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Cell Nuclei segmentation in Pap smear images using Optimized Binarization technique with Adaptive Wiener Filter

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Abstract

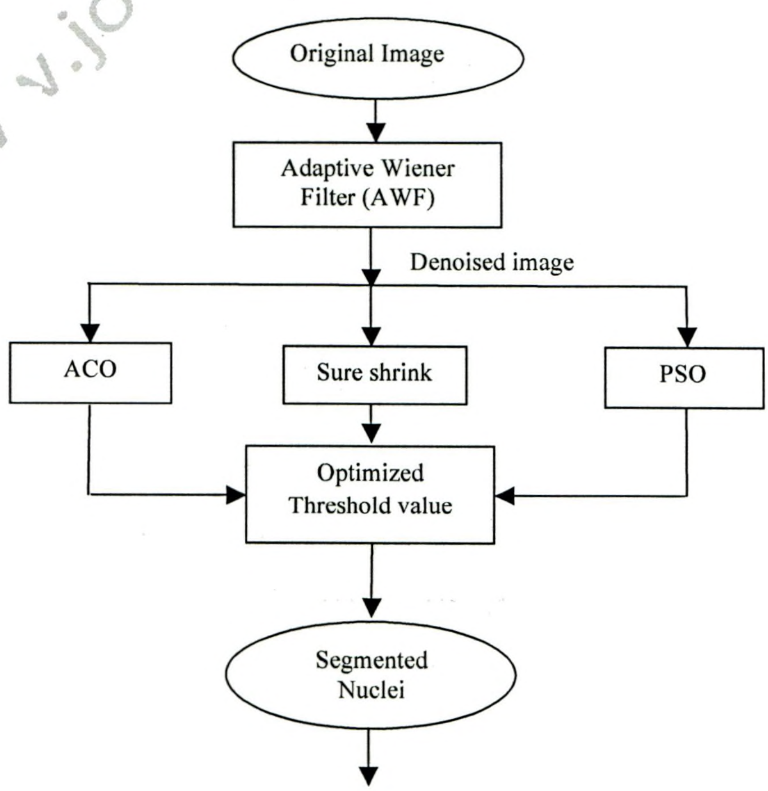
Cervical cancer is the second leading reason of death among women in India. The most common screening technique is Pap smear test which is used to detect abnormal growth of cervical cells at an early stage. The accuracy rate of cervical cancer diagnosis using Pap smear images depends on the segmentation of the cell nuclei. This paper proposes the optimized binarization technique with Adaptive Wiener Filter (AWF) for the cell nuclei segmentation in two key steps. First, the Adaptive Wiener Filter is used for the noise removal as well as to preserve the details of the Pap smear images. Followed by, the threshold value is being obtained from the sure shrinkage method, Ant Colony Optimization and Particle swarm optimization for the exact segmentation of cell nuclei from Pap smear images. Due to the limitations in the segmentation techniques, the loss of cell nuclei gets a raise which affects the quality and efficiency of cervical cancer detection. To know about the loss in the number of cell nuclei during segmentation step, the number of nuclei is counted from the segmented images and cell count results are compared with each other. From the results, it is found that the Adaptive Wiener Filter in combination with PSO based threshold segmentation performs well in terms of MSE, cell nuclei count, sensitivity and specificity.

Keywords- Cervical cancer, Adaptive Wiener Filter (AWF), Optimized threshold segmentation, Ant Colony Optimization, Particle swarm optimization

1. Introduction

In developing countries like India, cervical cancer is the most common gynaecological cancer and one of the most common cancers among women worldwide. It is caused by Human PapillomaVirus (HPV) infection. In 2004, cervical cancer was the third largest cause of cancer mortality in India with incidence rate of 30.7 per 100,000 women [1]. As of now, the incidence and mortality rates have decreased gradually over the past few decades, mainly due to the widespread use of the Pap smear test which detects cervical cancer and precancerous lesions easily and accurately.

Cervical screening using Pap smear images is one of the most successful ways of detecting and diagnosing the cancer even at an early pre-cancerous stage. However, Pap smear test does not always produce good diagnostic performance due to bad samples, technical and human errors [6]. Due to limitations of diagnosis performance by Pap smear test, computer aided visualization and intelligent diagnosis has to be developed to increase the diagnostic performance of the Pap smear test.



Performance Evaluation based on MSE, Cell Count, Sensitivity and Specificity

Fig.1: Block Diagram of proposed Cell Nuclei segmentation in Pap smear images

In this work, initially the original Pap smear image is given as input to the filter for the removal of noise from the original image. Next, the optimized threshold value is being obtained from ACO and PSO for the cell nuclei segmentation. Finally, the cell nuclei are segmented from the denoised images and performance evaluation is done.

The paper is structured as follows, the restoration procedure adopted in the work is detailed in the section 2, section 3 discusses the optimization of binarization technique for cell segmentation, section 4 discusses the performance evaluation results for the taken image dataset and section 5 gives the conclusion and followed by references used.

2. Suitable Restoration technique for Pap smear images filtering

Microscopic images are often corrupted by Poisson noise [8]. For the proper diagnosis of diseases, the pre-processing step in Pap smear images is vital to remove the noise and to increase the contrast. Removing noise from any processed images is very necessary. However, noise should be removed in such a way that essential information of image should be preserved. As per the result derived in the previous work with the same dataset, the Adaptive Wiener Filter (Wiener Filter) is the best filter to restore the original image which is corrupted by noise.

2.1 Adaptive Wiener Filter

The Adaptive Wiener Filter was proposed by Norbert Wiener in 1940 and its purpose is to reduce the amount of noise present in an image. It takes a statistical approach to solve its target. The aim of the process is to have minimum mean- square error. which means, the difference between the original signal and the new signal should be as less as possible.

Procedure for Adaptive Wiener Filter

Step 1: For the given input images, the local mean and variance around each pixel is calculated by using the following equation,

$$\mu = \frac{1}{NM}\sum_{n_1,} \propto (n_1, n_2) \quad \text{………………………………} (1)$$

$$\sigma^2 = \frac{1}{NM}\sum_{n_1,n_2\in n} a^2 (n_1, n_2) - \mu^2 \quad \text{…..………………………………} (2)$$

where, μ is the mean and σ^2 is the variance and $\curlywedge$ is the *N*-by-*M* local neighborhood of each pixel in the image.

Step 2: Local variance from the given image is obtained by applying wiener function in a linear filter.

Step 3: If the variance calculated for the given image is large, the wiener performs little smoothing.

Step 4: when the variance is small the wiener performs more smoothing.

The first step in the automatic segmentation of cell nuclei is the pre-processing of the Pap smear images. After the input image is read into memory, its size should be resized to 400*400 sizes. The resizing is done to preserve the image aspect ratio. Then an Adaptive Wiener Filter is applied to increase the contrast in bright cell regions and to remove noise from the image.

3. Optimization of binarization technique for cell segmentation

The correct characterization of Pap smear slides for the contents of the pap smear depends on the general appearance of the nuclei. This is based on the fact that the nucleus is an important structural part of the cell which exhibits significant changes when a cell is affected by a disease [6]. In pathological situations, the nucleus may exhibit disproportionate enlargement, irregularity in form and outline. The identification and quantification of these changes in the nucleus morphology and density contribute in the discrimination of normal and abnormal cells in Pap smear images. Segmentation of cells in cytological images is a fundamental subject of quantitative analysis. Because the malignant or abnormal characteristics of cancer cells are contained in cell nucleus, so the isolation of cell nucleus is an important task of segmentation.

3.1 Proposed Binarization Techniques

The proposed optimized threshold based segmentation method comprises of two subtasks,

(i) optimized threshold technique selection and

(ii) Applying that optimized threshold to the Pap smear images.

The selection of threshold is the most important step. In various application of medical image processing, the gray levels pixel intensity of nuclei is entirely different from the gray level intensity of the cytoplasm and backgrounds. So, the thresholding method will become a straightforward but successful tool to separate objects from the background. The performance measured and outcome of the optimized threshold based segmentation are shown in Fig.2, Fig.3, Fig.4 and Fig. 5.

3.1.1Particle swarm optimization (PSO)

PSO is the population based stochastic optimization technique. Firstly, based on the given input image, the particles position and velocity is initialized and the iteration count i is set as 1. Secondly, based on the particles position and velocity, the fitness value is calculated and result is stored. Next, the iteration count is incremented and also the particles position and velocity is updated. Based on the updated values, the fitness value is calculated and compared with the stored value. Finally, the threshold value is displayed when the iteration reaches the maximum. "In recent years this method has gained recognition over its competitors due to its simplicity, superior convergence characteristics and high solution quality" [7].

PSO Procedure

Step1: Initialize N particles with random positions x_1 , $x_2 \ldots x_N$ and velocities V_i where i=1,2,..N.

$$V_{ij}^{k+1} = wV_{i,j}^{k} + c_1 r_1 (pbest_{ij}^{k} - x_{ij}^{k}) + c_2 r_2 (gbest_{j}^{k} - x_{ij}^{k}) \quad \ldots\ldots\ldots\ldots\ldots \quad (3)$$

where, X and V represent the particle's position and its corresponding velocity in search space respectively with K iteration.

Step2: Velocity and position of each particle in next iterations is calculated using the Eq. (4).

$$x_{ij}^{k+1} = x_g^k + v_g^k \quad \ldots\ \ldots\ldots\ \ldots \quad (4)$$

Step3: Update global best positions.

If *f (pbesti) < f (xi),* then *pbesti = xi,* and search for the maximum value *fmax* among *f (pbesti),* If max *f (gbest) < fmax, ,then gbest = x max, xmax* is the particle associated with *fmax.*

Step4: Update velocity: update the *i*th particle velocity using the Eq. (4) restricted by maximum and minimum threshold *vmax* and *vmin* .

Step5: Repeat step 2 to 5, until the optimal solution is obtained.

3.1.2 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a pattern for designing metaheuristic algorithms for combinatorial optimization problems. Initially, the first ant is selected from the given input images. The path for each ant is selected on the basis of the amount of "pheromone trail" present on the possible paths starting from the current node of the ant. In case of equal or no pheromone on adjacent paths, ants randomly choose the path. Ant then reaches the next node and again does the path selection process. This process continues till the ant reaches the starting node. This finished tour gives the best threshold.

Ant colony optimization procedure

Step 1: Choose the first ant k=1

Step 2: Evaluate ant value.

If k(ant)<aver(ant), generate new ant k again.

Else transit to ant j (1<=j<= K) according to the transition rule

Step 3: In the neighbourhood of ant j with a radius of r, randomly search the better ant to update ant j. Copy the ant j to the best ant g if j(ant>g(ant). Update ant k with ant j

Step 4: Continue to choose the next ant k=k+1

Step 5: Update Pheromone and neighbour radius=0.9

Step 6: Return the best ant g.

3.1.3 Sure Shrink Algorithm

Sure shrink is a threshold selection method, in which a separate threshold is computed for each sub band. Next, it computes the value that minimizes Stein's Unbiased Risk Estimator, size of the image and noise variances to calculate the sure shrink threshold by using the soft thresholding rule.

Procedure

Step 1: The sure shrink threshold is calculated by using the formula

$$t^* = \min\left(t, \sigma\sqrt{2logn}\right) \quad \ldots\ldots\ldots\ldots\ldots (5)$$

where, t is the value that minimize Stein's Unbiased Risk Estimator , σ is the noise variance, n is the size of the images and t^* is the sure shrink threshold.

Step 2: Minimize the mean squared error by minimizing the function

$$f(\lambda) = N + ||g(x)||2 + \frac{2\Sigma d}{dxk(gk(x))} \quad \ldots\ldots\ldots\ldots\ldots (6)$$

where (x) is the threshold function minus the value for each value of , k = 1, 2, …N

Step 3: Once the size of the given image, noise variance and minimize Stein's Unbiased Risk Estimator is found. The sure shrink threshold is calculates and given as output.

4. Performance Evaluation

In this section, the result of the segmented nuclei which is obtained from the optimized threshold based segmentation is evaluated based on the subjective and objective evaluations. The subjective evaluation of segmented nuclei obtained using the proposed method is shown in Fig.2. Fig.3 shows the objective evaluation based on MSE, in view of the fact that their MSE is lower for AWF in combination with PSO based optimized threshold segmentation method. From the cell nuclei result, it is inferred that cell nuclei loss during segmentation is low for AWF in combination with PSO based optimized threshold segmentation method which is shown in fig.4. Even though the cell nuclei loss is high for AWF in combination with sure shrink based optimized threshold segmentation, the sensitivity and specificity remains high. So, AWF in combination with PSO based optimized threshold segmentation method is the best method for cell nuclei segmentation in Pap smear images due to the minimized cell nuclei loss.

4.1 MSE (Mean Square Error)

Mean Square Error (MSE) is one way of measuring the similarity to compute an error signal by subtracting the test signal from the reference, and then to compute the average energy of the error signal. The mean-squared-error (MSE) is the simplest, and the most widely used for image quality measurement.

$$\text{MSE}=\frac{1}{MN}\sum_{i=1} M \sum_{j=1} N(x(i,j) - y(i.j))^2 \quad \ldots\ldots\ldots\ldots\ldots (7)$$

Where x (i, j) represent the original image and y(i , j) represent the denoised (modified) image and i and j are the pixel position of the M×N image.MSE is zero when x(i, j) = y(i, j) .

4.2 Cell Nuclei count

To count the cell nuclei from all the segmented images, the cell nuclei's are counted manually from each of the resultant images and original images to yield a total cell nuclei count within an image. Then, the number of nuclei detected by the proposed segmentation technique is compared with the original images cell count. From the cell nuclei count results, it is inferred that the optimized threshold based AWF in combination with PSO shows good result when compared with other methods due to the minimum number of cell nuclei count loss during segmentation step.

4.3 Sensitivity and specificity

The fundamental measures to quantify the cell count accuracy of a test include sensitivity and specificity. The sensitivity of a nuclei segmentation test quantifies its ability to correctly identify nuclei as nuclei. It is the proportion of true positives that are correctly identified by the test, given by:

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad \dots\dots\dots (8)$$

The specificity is the ability of a test to correctly identify whether the artifacts are identified as nuclei. It is the proportion of true negatives that are correctly identified by the test, given by:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad \dots\dots\dots (9)$$

Original Images	Nuclei segmentation (AWF+Sure shrink based threshold)	Nuclei segmentation (AWF+ACO based threshold)	Nuclei segmentation (AWF+ PSO based threshold)

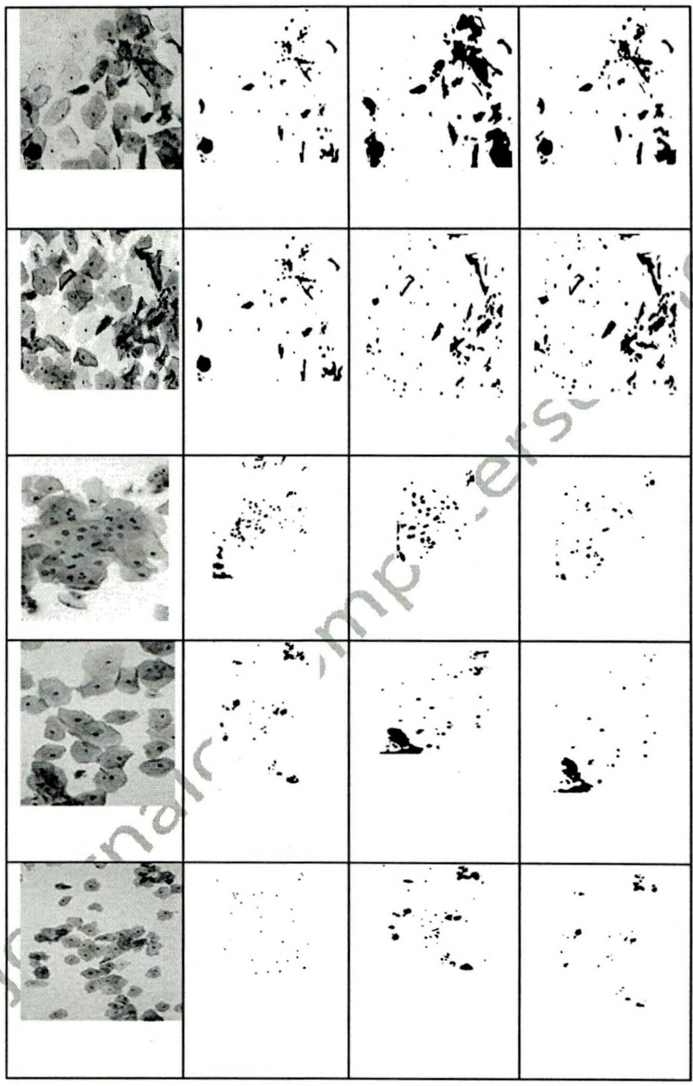


Fig.2: Subjective comparison results of original and segmented nuclei images using proposed techniques

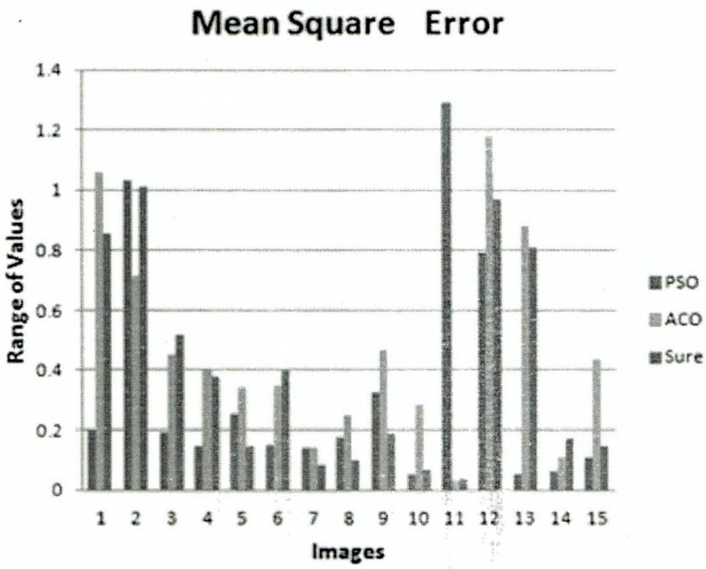
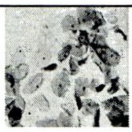
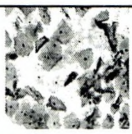


Fig 3: MSE metric comparison results for Adaptive Wiener Filter in combination with sure shrinkage method, ACO and PSO based threshold segmentation.

S.No	Images	Original Images [Nuclei count]	AWF+ Sure shrink based threshold [Nuclei count]	AWF+ ACO based threshold [Nuclei count]	AWF+ PSO based threshold [Nuclei count]
1		41	31	33	**39**
2		53	**49**	33	43
3		47	6	**34**	27

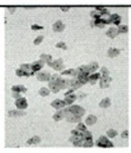
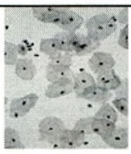
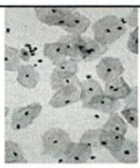
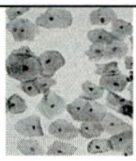
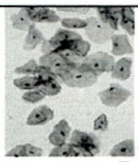
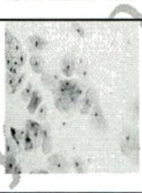
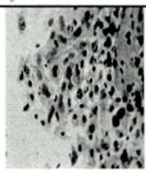
4		46	4	32	**38**
5		43	11	28	**34**
6		44	2	**37**	36
7		35	21	32	**34**
8		41	16	32	**36**
9		40	11	25	**32**
10		138	76	119	**124**

Fig.4: Comparison results of Adaptive Wiener Filter in combination with sure shrinkage, ACO and PSO based threshold segmentation in terms of cell count.

Performance Metrics	AWF+ Sure shrink based threshold [Nuclei count]	AWF+ ACO based threshold [Nuclei count]	AWF+ PSO based threshold [Nuclei count]
Sensitivity	0.462	0.217	0.248
Specificity	0.921	0.813	0.868

Fig.5: Sensitivity and Specificity values for Adaptive Wiener Filter in combination with sure shrink, ACO and PSO based threshold segmentation

5. Conclusion

This paper presented a comparison of optimized threshold based segmentation method by measuring their performance with evaluation metrics. In this paper, the Adaptive Wiener filter is used to restore the image from noise and for strengthening the segmentation method; an optimized threshold based segmentation method is used in combination with AWF for the exact cell nuclei segmentation. With this, the number of nuclei is counted manually from the segmented images to identify the cell nuclei loss during the segmentation step. From the MSE result, it is inferred that the AWF in combination with PSO based optimized threshold segmentation has smaller value. According to the cell nuclei count, the loss of cell nuclei during segmentation step is comparatively lesser than others with the specificity value of 0.217.

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